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Panel time series: Review of the methodological evolution

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Abstract. In this article, we discuss the econometric treatment of macropanel, also known as panel time series. This new approach rejects the assumption of slope homogeneity and handles nonstationarity. It also recognizes that cross-section dependence (that is, some correlation structure in the error term between units due to unobservable common factors) squanders efficiency gains by operating with a panel. This approach uses a new set of estimators known in the literature as the common correlated effect, which essentially consists of increasing the model to be fit by adding the averages of the individuals in each time t , of both the dependent variable and the specific regressors of each individual. We present two commands developed for the evaluation and treatment of cross-section dependence.

Keywords: st0439, xtcsi, xtcips, panel time series, time series, cross-section dependence

1 Introduction

Panel-data models became very popular in empirical econometrics in the late 20th century and the beginning of the 21st century, mainly because they can capture the heterogeneity of the agents' socioeconomic performance against both cross-section and time-series models.

Panel data¹ are used to describe various econometric situations. Basically, panel data consist of a sample of units² over time, and the data provide multiple observations for each unit using periodic surveys on families or companies. Panel-data models use either micropanel or macropanel. A micropanel consists of a large number of N units—hundreds or thousands—over a short period of time, from $T = 2$ observations per unit to a maximum of $T = 10/20$. In contrast, macropanel generally involve an N number of countries from a few nations (such as the G7 members to all countries of

1. Panel data may also be referred to as longitudinal data. The term used may vary depending on the discipline analyzing the data.

2. By units, we mean workers, families, companies, industries, regions, countries, etc.

the Penn World Table or the World Development Indicators), and the data are usually given quarterly or yearly, with ranges from 20 to 60 years (Arellano 2003; Hsiao 2014).

Micropanels and macropanels require different econometric treatment (Baltagi 2013). For instance, in micropanels, the asymptotic analysis must be performed for large N and fixed T ; in macropanels, the asymptotic analysis is performed allowing both N and T to tend to infinity (Phillips and Moon 1999). Likewise, a large T in a macropanel must deal with nonstationarity issues inherent in the time-series analysis.

The first theoretical developments involving panel data were applied to the treatment of micropanels. The panel-data literature in the second half of the 1980s and in most of the 1990s focused on the structure of micropanels (a large N and a small T). The fixed-effect estimator, the Anderson–Hsiao estimator, the Arellano and Bond estimator, or the system generalized method of moments estimators were conceived to address the design of the micropanel (see Arellano [2003]; Hsiao [2014]; Baltagi [2013]). However, in the late 1990s, the first articles were published to warn that the selection of the estimator crucially depends on the design of the panel (that is, on the relative size of N and T) (Pesaran and Smith 1995; Im, Pesaran, and Shin [IPS] 2003).

In this article, we focus on the econometric treatment of macropanels, known in the literature as “panel time series”. We introduce the main attributes of the panel time-series literature, and we present two new commands for evaluating and treating of cross-section dependence (CSD).

2 Panel time series

Concepts such as the purchasing power parity, the savings-to-investment ratio, or the problem of convergence in the theory of growth, among others, have benefited from using panels formed by countries with large T . The fact that T may tend to infinity contributed to the dramatic increase of the literature on panel data. The earliest literature rejected the assumption of homogeneity of slopes, as assumed in standard pooled estimators (fixed effects, difference, or system generalized method of moments), and proposed heterogeneous slopes (that is, a regression per unit³) (for example, see Pesaran and Smith [1995]; Pesaran, Shin, and Smith [1999]; and IPS [2003]). This literature is based on a T large enough to estimate each regression separately (that is, a regression per country).

Other literature focused on the time-series methods applied to a panel, dealing with nonstationarity, spurious regressions, and cointegration relationships. This work discussed how including the cross-section dimension in the time dimension offers important advantages when evaluating nonstationarity and cointegration. Confidence in the econometrics of nonstationarity panels lies in combining the best of both worlds: the treatment of nonstationarity according to time-series models and, simultaneously, the possibility to increase the data and the power of the tests based on the cross-section dimension. Particularly, adding the cross-section dimension under specific assumptions

3. See the user-written command `xtmg` by Eberhardt (2012).

may be interpreted as different samples of the same population distribution. By combining the time dimension with the cross-section dimension, one increases the power of the statistical tests, and the estimators may converge in distribution to normal random variables (Baltagi and Kao 2000).

As with the empirical analysis of time-series models, unit-root tests are now a frequent practice in panel models. In the late 1990s, the first panel unit-root tests were developed.⁴ Theoretically, these tests make different assumptions about the rates at which the number of units, N , and the numbers of time periods, T , tend to infinity or about whether N or T is fixed. The way in which N and T tend to infinity is critical when determining the asymptotic properties of the estimators and deciding which test is the most appropriate (Phillips and Moon 1999, 2000; LL 1992).⁵ The IPS (2003) test is one of the most widely used because it is less restrictive than that of Levin, Lin, and Chu (2002). According to IPS (2003), a sample of N units (countries) over T periods is considered, and the stochastic process y_{it} is generated by the following first-order autoregressive process with initial y_{it} values:

$$y_{it} = (1 - \phi_i)\mu_i + \phi_i y_{i,t-1} + \epsilon_{it} \quad i = 1, \dots, N \quad t = 1, \dots, T \quad (1)$$

As in the Dickey–Fuller (DF) test, the interest lies in testing the unit-root null hypothesis of $\phi_i = 1$ for every i (unit). The previous equation may be rewritten as

$$\Delta y_{it} = \alpha_i + \beta_i y_{i,t-1} + \epsilon_{it}$$

where

$$\begin{aligned} \alpha_i &= (1 - \phi_i)\mu_i \\ \beta_i &= -(1 - \phi_i) \end{aligned}$$

and

$$\Delta y_{it} = y_{it} - y_{i,t-1}$$

Then, the unit-root test is

$H_0: \beta_i = 0$ for all i , versus the alternatives

$H_1: \beta_i < 0, \quad i = 1, \dots, N_1, \quad \beta_i = 0, \quad i = N_1 + 1, N_1 + 2, \dots, N \quad 0 < N_1 \leq N$

The alternative hypothesis allows β_i to differ among units, unlike the homogeneous alternative of the test of Levin, Lin, and Chu (2002), which states $\beta_i = \beta < 0$ for every i . Likewise, the fraction of units following a stationary process is different from zero; that is, $\lim_{N \rightarrow \infty} (N_1/N) = \delta$, $0 < \delta \leq 1$. This condition is required for the consistency of the IPS test. The statistic proposed by IPS, \bar{t}_{IPS} , is defined as the average of the unit t statistics of the DF (augmented) regression.

4. The first test was used by Levin and Lin (LL, 1992) and was followed by the IPS (2003), Maddala and Wu (1999), Choi (2001), and Hadri (2000) tests.

5. For a detailed analysis of the asymptotic properties of different panel unit-root tests, see [XT] **xtunitroot**.

Maddala and Wu (1999) agree on the advantage of the heterogeneous alternative of IPS, but they highlight that averaging DF statistics is not the most efficient way to use information. Following Fisher (1932), they propose a statistical test that is an average of the logarithms of the p -values associated with statistic t in each unit. According to his simulations, in several situations, the Maddala and Wu test performs better (both in terms of size and power) than the IPS test, which, in turn, is more powerful than the LL test (Smith and Fuertes 2010). On the other hand, Breitung (2000) uses Monte Carlo simulations to study the power of the LL and IPS tests and finds a dramatic loss of power in both tests when deterministic terms are included.

Breitung and Pesaran (2008) discuss the evolution of panel unit-root tests. They highlight that one of the primary objectives when using these panel tests is to improve the poor performance of time-series unit-root tests. For instance, the augmented DF test generally does not reject the null hypothesis that the real exchange rate is non-stationary. However, the panel unit-root tests applied to an ensemble of industrialized countries generally reject the hypothesis of one unit root—that is, the real exchange rate shows a stationary behavior, empirically supporting the purchasing power parity (Coakley and Fuertes 1997).

Although panel unit-root tests were conceived to correct the lack of power in time-series tests, they also caused several inconveniences. One key assumption of panel unit-root tests is the independence of units, which is an essential condition for the average statistic of unit DFs, \bar{t}_{IPS} , to converge to the normal distribution.⁶ Furthermore, if the unit-root null hypothesis is rejected, then interpreting this result becomes more difficult because the best conclusion we may draw is that a fraction of units is stationary. Nothing can be stated about how many units there are or which units are stationary.

One reason why empirical research is concerned about the presence of unit roots in time-series models is to avoid the problem of spurious correlation. As is well known, cointegration is required among variables $I(1)$ for the regression not to be spurious and for the estimator of interest to be consistent. This means that if the variables are cointegrated, then they share a common stochastic trend that is canceled in their linear combination. Pesaran and Smith (1995) indicate that spurious regression does not arise in a cross-section regression when the time dimension collapses, even when the time series of each unit has a unit root.⁷ As a result of this observation, the problem of spurious correlation was largely mitigated by averaging the units. Phillips and Moon (1999, 2000), Pedroni (1996, 1997b,a), and Kao and Chiang (2000) show that the mean group (MG) estimator that they propose is more efficient than the estimator given by a cross-section regression.

Panel-cointegration models are used to study long-term economic relationships, which are typical in macroeconomic and financial data analysis. These long-term relationships are frequently predicted by economic theory. Consequently, empirical re-

6. The assumption of independence of the units is critical to meet the requirements of the Linderberg-Levy central limit theorem in the elaboration of the unit-root statistic and of the estimators and tests that are an average of individual relationships (Baltagi and Kao 2000).

7. See the user-written command `xtpmg` by Blackburne and Frank (2007).

search is interested in the estimation of regression coefficients to then evaluate if the theoretical restrictions are satisfied. [Kao and Chen \(1995\)](#) show that the ordinary least-squares (OLS) estimator in the cointegrated panel is asymptotically normal but biased. [Chen, McCoskey, and Kao \(1999\)](#) find that the OLS estimator corrected for bias does not improve the results relative to the general OLS estimator. The authors suggest using the fully modified OLS (FMOLS) estimator or the dynamic OLS estimator. [Phillips and Moon \(1999\)](#) and [Pedroni \(1996\)](#) propose the fully modified (FM) estimator as a generalization of the [Phillips and Hansen \(1990\)](#) estimator. [Kao and Chiang \(2000\)](#) study the limit distribution in a cointegration regression according to the FM estimator and show that it is asymptotically normal.

Likewise, [Pedroni \(1996\)](#) and [Phillips and Moon \(1999\)](#) also obtain similar results for the limit distribution of the FM estimator. Phillips and Moon (1999) analyze the different types of relationships present in nonstationary panels.⁸ The authors require that $N/T \rightarrow 0$; consequently, the results are valid for panels with moderate N and large T (that is, macropanel) but not for panels with moderate T and large N (typical micropanel). Within possible estimators, the MG estimator proposed by [Pesaran and Smith \(1995\)](#), also called the average long-run estimator by [Phillips and Moon \(1999, 2000\)](#), estimates the time-series model $y_{it} = \eta_i + \lambda_i x_{it} + u_{it}$ for each country and then obtains the $\hat{\lambda}$, as $\hat{\lambda} = \sum_i \hat{\lambda}_i / N$. Likewise, $E(\hat{\lambda}_i) = \lambda$ represents the average behavior of the countries. The MG estimator is consistent even when the $\hat{\lambda}_i$ are not.

As it occurs with unit-root tests mentioned above, the key to obtaining the consistent estimators is the independence of cross-section units so as to add information when averaging the estimated parameters that result from the unit time-series analysis, thus mitigating the virtual spurious correlation. [Phillips and Moon \(1999, 2000\)](#) propose a variation for the MG estimator, which they call the FMOLS. Apart from its capacity to consider heterogeneity among the panel units, the FMOLS estimator can control for the bias induced by the potential endogeneity of regressors and the serial correlation and heteroskedasticity of residuals ([Pedroni 2000, 2001, 2007](#)).⁹

One interesting result of nonstationary panels is that several statistical tests and estimators converge to the normal distribution. This applies to the above-mentioned distribution of the IPS statistic and to the FM and dynamic OLS estimators ([Kao and Chiang 2000](#)). This asymptotic convergence contrasts markedly with the unit-root test behavior and the spurious correlation problems of time-series models.

8. The authors allow the series under analysis to cointegrate or not, and they introduce a framework for the sequential and joint study of the asymptotic theory in nonstationary panels. The panel model considers the following four cases: 1) spurious regression in panel data, where there is no cointegration among series; 2) heterogeneous cointegration in panel data, where each unit has its own cointegration relationship; 3) homogeneous cointegration in panel data; and 4) near-homogeneous cointegration in panel data.

9. While the MG estimator uses parametric short-term dynamics, the FM estimator is based on nonparametric methods to eliminate the effects of dynamics and any type of endogeneity of the residuals on long-term coefficients ([Smith and Fuertes 2010](#)). The estimator is highly consistent under cointegration and robust when there are omitted variables that are not part of the cointegration relationship ([Pedroni 2007](#)).

The econometric theory developed so far for panel unit-root tests and the asymptotic convergence to normal distribution of the proposed estimators that entail heterogeneous slopes was based on the independence of the units (countries) of the panel, a situation rarely seen in the empirical study of macropanel. The lack of independence among units is known in the literature as CSD, and its presence is natural in the study of these types of data, such as the global economic and financial cycle through the globalization of economic activity, the common trade areas, technological progress, and the spillover effects. Disregarding the CSD—that is, some correlation structure in the error term between units due to unobservable common factors—squanders the efficiency gains of operating with a panel and leads to inconsistent estimators of the parameters, thus invalidating the theoretical inference in panel-data models (Kapetanios, Pesaran, and Yamagata 2011; Banerjee and Carrion-i-Silvestre 2011). Note that unobservable common factors are nothing but variables that have been omitted in the specification of the model to be fit.

Empirical researchers first incorporated time dummies to deal with the lack of independence among units and to remove unobservable common factors. Nevertheless, this solution assumed slopes to be homogeneous; that is, $\lambda_i = \lambda$. Another proposal consisted in deducting the corresponding mean from each variable (that is, $\tilde{y}_{it} = y_{it} - \bar{y}_t$, where $\bar{y}_t = \sum_{i=1}^N y_{it}/N$) and similarly from regressors, x_{it} . This process is known as de-meaning. But once again, one can prove that this potential solution for estimating unobservable factors requires an assumption of homogeneity in the impact of unobservable factors on units.

To model the CSD, one estimates the unobservable common factors by using the principal components techniques (Coakley, Fuertes, and Smith 2002; Bai 2004; Bai and Ng 2004). Pesaran (2006) refutes the proposal of principal components for estimating the CSD made by Coakley, Fuertes, and Smith (2002) and shows that a linear combination of unobservable common factors can be proxied using the averages on the units of the model regressors and of the dependent variable. This led to a new set of estimators known in the literature as the common correlated effect (CCE).¹⁰ CCE essentially consists of increasing the model to be fit by including the average of the units in each t of time, both of the dependent variable and of the specific regressors of each unit.

One can illustrate different intensities in the types of CSD manifestations such as neighborhood effects, network effects, the influence of a dominant unit, or simply unobservable common factors.¹¹ According to Pesaran (2006), the econometric model can be represented as

$$\begin{aligned} y_{it} &= \eta'_i z_t + \lambda'_i x_{it} + e_{it} \quad i = 1, \dots, N \quad t = 1, \dots, T \\ e_{it} &= \gamma'_i f_t + \epsilon_{it} \end{aligned} \quad (2)$$

10. See the user-written command `xtcce` for CCE estimation for static and dynamic panels with cross-sectional dependence.

11. There are two types of CSDs: weak and strong. The weak CSD implies that dependencies are of a local nature and decline with N . This may be true of spatial correlations, where each unit is correlated with only its neighbors, while the strong CSD implies that the dependence affects all the units.

where y_{it} is the observation of the i th unit at moment t ; z_t is a $k_z \times 1$ vector of the variables that do not differ over units (that is, the y intercept, trend, or seasonal dummies); x_{it} is a $k_x \times 1$ vector of observable regressors specific to each unit at moment t ; f_t is a $r \times 1$ vector of unobservable factors that may affect each unit differently and may be correlated with x_{it} ; and ϵ_{it} is the unobservable disturbance with $E(\epsilon_{it}) = 0$, $E(\epsilon_{it}^2) = \sigma_i^2$, which is independently distributed through i and t . The covariance between errors, e_{it} , is determined by the loading factor, γ_i . If f_t is correlated with x_{it} —as is generally the case in many empirical applications, such as global cycles—then disregarding the CSD by omitting factor f_t results in biased and inconsistent λ_i estimators.

Pesaran (2006) proposed to treat the unobservable factors as the nuisance parameters that we want to control for to get a better estimate of λ_i . The estimator proposed, the CCE, seeks to enrich the model to be fit by including cross-section averages in each t of time to control for the unobservable factors. This involves both independent and dependent variables, as follows:

$$y_{it} = \eta'_i z_t + \lambda'_i x_{it} + \delta_{oi} \bar{y}_t + \delta'_i \bar{x}_t + u_{it}$$

To understand the motivation of this procedure, let's assume one single factor and make an average of (2) on the units:

$$\begin{aligned} \bar{y}_t &= \bar{\eta}' z_t + \bar{\lambda}' \bar{x}_t + \bar{\gamma} f_t + \bar{\epsilon}_t + \frac{1}{N} \sum (\lambda_i - \bar{\lambda})' x_{it} \\ f_t &= \bar{\gamma}^{-1} \left[\bar{y}_t - \left\{ \bar{\eta}' z_t + \bar{\lambda}' \bar{x}_t + \bar{\epsilon}_t + \frac{1}{N} \sum (\lambda_i - \bar{\lambda})' x_{it} \right\} \right] \end{aligned}$$

Then, \bar{y}_t and \bar{x}_t operate as proxy of the unobservable factor. Note that the covariance between \bar{y}_t and ϵ_{it} tends to zero with N ; consequently, for a large N , there are no endogeneity problems. This formulation presupposes the existence of heterogeneous coefficients, but there are also homogeneous versions of them (see Eberhardt and Teal [2011]). This idea of incorporating the averages to the regressions per country is also used by Pesaran (2007) to immunize the IPS unit-root test against the presence of unobservable factors. These unit-root tests that control for the CSD are known as second-generation tests.

In addition to the heterogeneity on the observable regressors, Pesaran (2006) permits i) that unobservable common effects may affect units differently; ii) that errors per unit may show a serial correlation and heteroskedasticity; and iii) that it is not necessary for individual-specific regressors to be identical or to be distributed independently through the individuals, a relevant feature in country-panel analysis. However, Pesaran (2006) presupposes that both individual-specific regressors and common unobservable factors are stationary and exogenous. Kapetanios, Pesaran, and Yamagata (2011) extend this analysis and include $I(1)$ processes of the individual-specific regressors and of the unobservable effects. The extension is far from trivial and resorts to very different intermediate results to obtain the asymptotic distribution of the estimators when data are $I(1)$ versus when data are $I(0)$. But, surprisingly, Monte Carlo simulations suggest that the CCE method proposed by Pesaran (2006) to address CSD is robust for many

data-generating processes. This result is quite dissimilar in terms of the substantial differences inherent in time-series models for the distribution of $I(1)$ processes versus $I(0)$ processes.

Although this second generation of unit-root tests considered the lack of independence of the units when admitting the presence of unobservable common factors, it led to new challenges when interpreting both the unit-root test and the cointegration test (Breitung and Pesaran 2008). These unobservable common factors may exhibit a stationary behavior (for example, global economic cycles) or a nonstationary behavior (for example, global technological progress). If the unobservable factor exhibits a $I(1)$ behavior (that is, it reveals a unit root), then we should consider the possibility that this factor may cointegrate inside each unit and also between units. This is why the interpretation of the second-generation unit-root tests differs from the standard interpretation of a unit-root test.

Let's go back to (1), but we will now consider the unobservable factor:

$$y_{it} = (1 - \phi_i)\mu_i + \phi_i y_{i,t-1} + \gamma_i f_t + \epsilon_{it} \quad i = 1, \dots, N \quad t = 1, \dots, T$$

Rejecting the null hypothesis $\phi_i = 1$ in favor of the alternative $\phi_i < 1$ might be for very different reasons. It might be due to i) both y_{it} and f_t being stationary processes or to ii) y_{it} and f_t being $I(1)$ and cointegrated. And this is independent from the method used to account for the CSD.

Let's return to the solution offered by Pesaran (2006), the CCE, to control for the presence of the CSD, which was extended to the unit-root tests by Pesaran (2007) and Pesaran, Smith, and Yamagata (2013). The relevant equation to evaluate the presence of a unit root is

$$\Delta y_{it} = \alpha_i + \beta_i y_{i,t-1} + \delta_{0i} \overline{\Delta y_t} + \delta_{1i} \overline{y_{t-1}} + \epsilon_{it}, \quad i = 1, \dots, N \quad t = 1, \dots, T \quad (3)$$

that is, the conventional equation augmented by the averages of the units of both the regressor, y_{it} , and the dependent variable Δy_{it} . The hypothesis would consist in evaluating $\beta_i = 0$ using a panel test. Like the IPS (2003), the proposal of Pesaran (2007) consists in averaging the t_i statistics corresponding to β_i of (3). The new statistic, called the cross-sectional Im, Pesaran, and Shin (CIPS) by Pesaran, has a nonstandard distribution, even with a large N . This is different from the result obtained by IPS (2003), in which, under the assumption of the independence of units, the IPS statistic is distributed according to a normal distribution for a large N .

Note that (3) might be considered a correction-toward-equilibrium model, where $\overline{y_t}$ and y_{it} might be $I(1)$ despite $\beta_i < 0$, simply because they are cointegrated. The latter discourages the use of a panel unit-root test because interpretation can become more difficult. Under both H_0 and the alternative, we would face joint hypotheses. Under H_0 , a simultaneous evaluation reveals that all units are $I(1)$ and that they do not cointegrate, while the alternative reveals that $\beta_i < 0$, with the possibility that $y_{it} \sim I(1)$ may cointegrate with the unobservable factor.

To summarize, this new approach of time-series panel econometrics combines the two discussed lines of work proposed by the end of the 1990s. The questioning of parameter homogeneity of a macropanel model may come from the impact of both the observable factors (the regressors) and unobservable factors (the factor loadings). Ignoring the potential heterogeneity of both observable regressors and unobservable factors may have more serious implications if the observable variables or the unobservable factors are nonstationary. The following example illustrates this: an equation in levels estimated through a standard pooled estimator imposes common parameters for all countries and, at the same time, leads to nonstationary errors if the true parameters of the model are heterogeneous and the variables are nonstationary (Eberhardt and Teal 2011). Specifically, disregarding the heterogeneity of the model's observable regressor's parameters may disrupt the cointegration relationship between the regressors and the dependent variable and may produce spurious results (Smith and Fuertes 2010). Similarly, an equation in levels estimated through a standard pooled estimator and augmented with $T - 1$ dummy variables imposes a common evolution of unobservable factors to all countries, which creates stationary errors if the true unobservable factors exhibit a nonstationary behavior.

3 Evaluation of CSD: xtcsi

Although the CSD is a fact rather than an exception in macropanels, there are several tests for its evaluation. The Lagrange multiplier (LM) test of Breusch and Pagan (1980) could be one such test. It consists in the average of the squared pairwise correlation coefficients of the residuals and was designed using apparently nonrelated equations, or seemingly unrelated regression (Zellner 1962), with a fixed N and $T \rightarrow \infty$ (that is, a small N relative to T). Pesaran (2004) shows that the LM test exhibits serious size distortions when N is large relative to T , a situation easily observed in many empirical applications. To overcome the LM test bias, Pesaran (2004) proposes another test that he calls CD, which consists in averaging the pairwise correlations of the residuals. Under the null hypothesis, for a sufficiently large T , the CD statistic converges in distribution to $N(0, 1)$, when $N \rightarrow \infty$. However, as Pesaran (2004) notes, the CD test may be inconsistent in several relevant alternatives.

Based on Breusch–Pagan's LM test, Pesaran, Ullah, and Yamagata (2008) propose a new LM test that corrects the bias of the previous one in panels with strictly exogenous regressors and normal errors. Monte Carlo simulations analyze the power and size of the three available statistics. The authors conclude that the bias-adjusted LM test successfully controls for the size of the test and keeps a reasonable power.

Following Pesaran, Ullah, and Yamagata (2008), we have designed the `xtcsi` command, which computes the above mentioned three statistics as follows:

Consider the following panel-data model

$$y_{it} = \lambda'_i x_{it} + u_{it}, \text{ for } i = 1, 2, \dots, N; \quad t = 1, 2, \dots, T \quad (4)$$

where the $X_i = (x_{i1}, \dots, x_{iT})'$ matrix of regressors may contain the unit vector for the constant in the first column and a trend in the second column.¹² For each i , $u_{it} \sim \text{IIDN}(0, \sigma_{ui}^2)$. For every t , however, they might be cross-section correlated.

Breusch and Pagan (1980) propose the following LM statistic for testing the null of zero cross-equation error correlations:

$$\text{LM} = T \sum_{i=1}^{N-1} \sum_{j=i+1}^N \hat{\rho}_{ij}^2$$

Here $\hat{\rho}_{ij}$ is the sample estimate of the pairwise correlation of the residuals arising from the Monte Carlo optimization estimate of the regression for each unit of the panel.

Under the null hypothesis,

$$H_0: \text{Cov}(u_{it}, u_{jt}) = 0 \quad \text{for all } t \text{ and } i \neq j \quad (5)$$

The LM statistic is distributed asymptotically as a chi-squared with $N(N-1)/2$ degrees of freedom. However, the LM test may exhibit substantial distortions of size for large N and small T , a frequent situation in empirical applications.

Ullah (2004) offers unified techniques to obtain the exact and approximate moments of the econometric estimators and statistical tests. Pesaran, Ullah, and Yamagata (2008) use this approach to correct the bias in small samples of the LM statistic.

Assume the following:

Assumption 1: For each i , the disturbances, u_{it} , are serially independent with the mean 0 and the variance $0 < \sigma_i^2 < \infty$.

Assumption 2: Under the null hypothesis defined by $H_0: u_{it} = \sigma_i \epsilon_{it}$, $\epsilon_{it} \sim \text{IIDN}(0, 1)$ for all i and t .

Assumption 3: The regressors, x_{it} , are strictly exogenous such that $E(u_{it}/X_i) = 0$ for all i and t , where $X_i = (x_{i1}, \dots, x_{iT})'$ and $X_i'X_i$ is a positive defined matrix.

The authors introduce the following idempotent matrix of rank $T - k$:

$$M_i = I_T - H_i; \quad H_i = X_i(X_i'X_i)^{-1}X_i'$$

Considering (4) and under assumptions 1 to 3, the exact mean and variance of $(T - k)\hat{\rho}_{ij}^2$ are, respectively, given by

$$\mu_{Tij} = E\{(T - k)\hat{\rho}_{ij}^2\} = \frac{1}{T - k} \text{Tr}\{E(M_i M_j)\} \quad (6)$$

12. We include the constant and the trend in the X_i matrix [unlike that illustrated in (2), where both appeared explicitly in the Z_t matrix] to simplify the matrix calculation used to obtain the LM_{adj} statistic.

and

$$v_{Tij}^2 \text{Var} \{(T-k)\hat{\rho}_{ij}^2\} = [Tr \{E(M_i M_j)\}]^2 a_{1T} + 2Tr \{E[(M_i M_j)^2]\} a_{2T} \quad (7)$$

where

$$a_{1T} = a_{2T} - \frac{1}{(T-k)^2}, \quad a_{2T} = 3 \left\{ \frac{(T-k-8)(T-k+2) + 24}{(T-k+2)(T-k-2)(T-k-4)} \right\}^2$$

Using (6) and (7), we define the bias-adjusted LM statistical test as

$$\text{LM}_{\text{adj}} = \sqrt{\frac{2}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^N \frac{(T-k)\hat{\rho}_{ij}^2 - \mu_{Tij}}{v_{Tij}} \quad (8)$$

Under assumptions 1 to 3 and assuming that H_0 is defined by (5), $T \rightarrow \infty$ and then $N \rightarrow \infty$, we have

$$\text{LM}_{\text{adj}} \rightarrow_d N(0, 1)$$

To deal with the large N bias of the LM test, Pesaran (2004) suggests using the CD statistic defined by

$$\text{CD} = \sqrt{\frac{2T}{N(N-1)}} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^N \hat{\rho}_{ij} \right)$$

and shows that under H_0 and for sufficiently large T , $\text{CD} \rightarrow_d N(0, 1)$ as $N \rightarrow \infty$.

The test proposed by Pesaran, Ullah, and Yamagata (2008) is reported for balanced panels. According to Yamagata, the bias-adjusted test to the unbalanced panels case can be extended as follows: suppose we are considering two units (unit i and unit j), and suppose that y_{it} and x_{it} are observed between $[\text{date}_1, \text{date}_2]$, that y_{jt} and x_{jt} are observed between $[\text{date}'_1, \text{date}'_2]$, and that both have some overlapping period $[\text{date}''_1, \text{date}''_2]$, where $\text{date}''_1 = \max(\text{date}_1, \text{date}'_1)$ and $\text{date}''_2 = \min(\text{date}_2, \text{date}'_2)$. Then, the $\hat{\rho}_{ij}$ will be based on the residual regressions of y_{it} on x_{it} and y_{jt} on x_{jt} between the overlapping sample. Thus mean and variance adjustments as well as “ T ” in (8) should be adjusted appropriately (that is, these can be different for each combination of i and j).

3.1 Syntax

```
xtcsi depvar indepvars [if] [in] [, trend]
```

3.2 Description

`xtcsi` implements several error cross-section independence tests in (balanced) heterogeneous panels. These tests include the LM test by Breusch and Pagan (1980); the bias-adjusted LM test by Pesaran, Ullah, and Yamagata (2008); and the CD test by Pesaran (2004).

3.3 Option

`trend` specifies a linear trend to be included in each individual regression model.

3.4 Stored results

`xtcsi` stores the following in `r()`:

Scalars

<code>r(N_g)</code>	number of units of the panel
<code>r(lm)</code>	Breusch and Pagan (1980) LM test statistic
<code>r(p_lm)</code>	p -value of chi-squared with $N(N - 1)/2$ degrees of freedom
<code>r(lm_adj)</code>	Pesaran, Ullah, and Yamagata (2008) bias-adjusted LM test statistic
<code>r(p_lm_adj)</code>	two-sided p -value of normal (0, 1)
<code>r(lm_cd)</code>	Pesaran (2004) CD test statistic
<code>r(p_lm_cd)</code>	two-sided p -value of normal (0, 1)

3.5 Empirical example: `xtcsi`

Here we illustrate `xtcsi`. To evaluate the null hypothesis of no correlation among units, we take data from [Katz \(2014\)](#) on the determinants of foreign direct investment flows in eight Latin American countries during 1981–2012. Following his article, the dependent variable is the foreign direct investment as a percentage of gross domestic product (GDP) (`lfdi_gdp_1`), while the regressors are the change in the GDP per capita (`dlgdp_pc`), the change in the consumer price index (`infla`), the real exchange rate (`ltcr`), the terms of trade (`ltot`), and the rule of law (`rule_of_law`) and openness (`laper_gdp`). All variables are in logs but rule of law.

```
. use b_csd.dta
. tsset id year, y
      panel variable: id (strongly balanced)
      time variable: year, 1981 to 2012
              delta: 1 year
. xtcsl lfdi_gdp_1 dlgdp_pc infla ltcr ltot rule_of_law_1 laper_gdp, trend
Bias-adjusted LM test of error cross-section independence
H0: Cov(uit,ujt) = 0 for all t and i!=j
```

Test	Statistic	p-value
LM	25.9	0.5786
LM adj*	-2.077	0.0378
LM CD*	.6665	0.5051

*two-sided test

Test results show that while LM and LM CD cannot reject the null hypothesis of no correlation among the countries for all t , the bias-adjusted LM test by [Pesaran, Ullah, and Yamagata \(2008\)](#) rejects it at a confidence level of 3.8%

4 IPS test in the presence of the CSD: `xtcips`

Following [Pesaran \(2007\)](#), we used Stata to implement the CIPS test and the CIPS* test (a truncated alternative of the CIPS), which we called `xtcips`. As previously mentioned, the limit distribution of the CIPS statistic is not normal, and the corresponding critical values are tabulated in [Pesaran \(2007\)](#). The command is designed for balanced panels but may be adapted for unbalanced panels, although this would imply making a Monte Carlo simulation to obtain the critical values according to the panel structure. This is precisely what [Bebczuk, Burdisso, and Sangiácomo \(2012\)](#) do.

A simple guideline for obtaining the critical values for an unbalanced panel is to replicate the panel's structure. For example, suppose there are N cross-section units with a varying number of observations, $T_1, T_2 \dots T_N$. We then perform the following steps:

1. Generate a $T_1, T_2 \dots T_N$ nonstationary series, $y_1, y_2 \dots y_n$. For example, $y_{1t} = y_{1t-1} + u_{1t}$ $t = 1, 2, \dots, T_1$, and u_1 is from a standard normal process.
2. Compute $CADF_i$ for each unit.
3. Compute the t -bar (the average of $CADF_i$) according to [Pesaran \(2007\)](#) and keep it.
4. Repeat steps 1–3 10,000 times.
5. Obtain the 1%, 5%, and 10% quantiles for the sample distribution of t -bars.

Nevertheless, as mentioned previously, the command is designed for balanced panels.

4.1 Syntax

```
xtcips varname [if] [in], maxlags(#) bglags(numlist) [q trend noc]
```

`xtcips` is used with balanced panel data. You must `tsset` your data before using `xtcips` with the panel form of `tsset`; see `help tsset`. `varname` may contain time-series operators; see `help tsvarlist`.

4.2 Description

`xtcips` estimates the unit-root CIPS test in heterogeneous (balanced) panels developed by [Pesaran \(2007, sec. 4, 275–279\)](#).

There are three possible specifications:

Case I: models without an intercept or trend (see the `noc` option)

Case II: models with an individual-specific intercept (default)

Case III: models with an incidental linear trend (see the `trend` option)

The command allows the user to define individual dynamic specifications in each regression using two alternative criteria (see the `maxlags(#)` option):

- i) the Wald test of compound linear hypothesis on the model parameters (default)
- ii) the Portmanteau test (Q) of white noise (see the `q` option)

`xtcips` reports the p -value of the LM test on the Breusch–Godfrey serial correlation of each individual regression (see the `bglags()` option).

The null hypothesis is (homogeneous nonstationary)

$$H_0: \beta_i = 0 \text{ for all } i$$

versus the alternatives

$$H_1: \beta_i < 0, \quad i = 1, \dots, N_i, \quad \beta_i = 0, \quad i = N_1 + 1, N_1 + 2, \dots, N$$

in the following regression of the cross-section augmented DF (CADF) test:

$$\Delta y_{it} = \alpha_i + \beta_i y_{i,t-1} + \delta_{0i} \Delta \bar{y}_t + \delta_{1i} \bar{y}_{t-1} + \epsilon_{it}, \quad i = 1, \dots, N \quad t = 1, \dots, T$$

4.3 Options

`maxlags(#)` defines the individual dynamic specification and specifies the maximum number of lags to be included in the model to be estimated for each unit. Then, `xtcips` determines the number of lags to be included in each individual regression with an iterative process of 0 to `maxlags()` based on the level of significance of the test established to select the dynamics. This may be done by selecting the highest significant lag, either i) by rejecting H_0 (at 5% or lower) in the Wald test¹³ or ii) by not rejecting H_0 (at 95% or higher) in the Portmanteau test (Q) of white noise or `maxlags()`, whichever occurs first. `maxlags()` is required and must be a positive integer.

`bglags(numlist)` establishes the serial correlation order to be tested in the LM test by Breusch–Godfrey in each individual regression. If only one value is provided (a positive integer), then that order is used for all units. If a list of numbers is provided, its length must match the number of units in the panel. `bglags()` is required.

13. The model is estimated with the number of lags specified according to `maxlags(L)`, and the steps for performing the Wald test are as follows. Test the null hypothesis of the test $H_0: \delta_{0i}^1 = \delta_{0i}^2 = \delta_{0i}^3 = \dots = \delta_{0i}^L = \delta_{1i}^1 = \delta_{1i}^2 = \delta_{1i}^3 = \dots = \delta_{1i}^L = 0$. If H_0 is not rejected, then the specification suggested would be the standard DF without augmenting. If H_0 is rejected, then $H_0: \delta_{0i}^2 = \delta_{0i}^3 = \dots = \delta_{0i}^L = \delta_{1i}^2 = \delta_{1i}^3 = \dots = \delta_{1i}^L = 0$ is tested. If H_0 is not rejected, the specification suggested would be the DF augmented by one lag. If H_0 is rejected, the same procedure applies until the maximum lag for the specified `maxlags(L)` is determined.

q establishes the Portmanteau (Q) test of white noise as the criterion to determine the dynamic specification.

trend includes a time trend in the estimated equation (case III).

noc eliminates the constant term (case I).

4.4 Stored results

xtcips stores the following in **r()**:

Scalars

r(cips) CIPS statistic

Matrices

r(cv) critical values of average of individual cross-sectionally augmented DF distribution

r(W) individual regression diagnostics

4.5 Empirical example: **xtcips**

In this section, we illustrate **xtcips**. With the same dataset used in section 3.5, we evaluate the presence of a unit root for the log of foreign direct investment as %GDP (**lfdi_gdp_1**) when we consider the CSD.

```
. use b_csd.dta, clear
. tsset id year, y
    panel variable: id (strongly balanced)
    time variable: year, 1981 to 2012
    delta: 1 year
. xtcips lfdi_gdp_1, maxl(5) bglag(1) trend
Pesaran Panel Unit Root Test with cross-sectional and first difference mean
> included for lfdi_gdp_1
Deterministics chosen: constant & trend
Dynamics: lags criterion decision General to Particular based on F joint test
H0 (homogeneous non-stationary): bi = 0 for all i
CIPS =      -3.920      N,T = (8,32)
```

	10%	5%	1%
Critical values at	-2.71	-2.86	-3.15

As can be seen, the statistic value is -3.92 , which is below the critical value at the 1% significance level. Thus this second-generation test rejects the null hypothesis of a unit-root process for the foreign direct investment as a percentage of GDP.

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